New Estimates of Soil and Biomass Carbon Stocks for Global Economic Models

By

Holly Gibbs[1]

Sahoko Yui[2]

Richard Plevin[3]

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[1] University of Wisconsin-Madison, Department of Geography and the Nelson Institute for Environmental Studies' Center for Sustainability and the Global Environment (SAGE). Corresponding author hkgibbs@wisc,edu
[2] University of California-Davis, Institute of Transportation Studies
[3] University of California-Davis, Institute of Transportation Studies

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ABSTRACT

We synthesized a range of geographically-explicit forest, grassland and cropland biomass and soil carbon input data sources and used geographic information systems (GIS) software to calculate new estimates of soil and biomass carbon stocks for use with global economic models, particularly for the Global Trade and Analysis Project (GTAP). Our results quantify the average amount of carbon stored in soil and biomass in each of the 246 countries, stratified by agro-ecological zones (available in the accompanying spreadsheet). We also provide the data aggregated to the 134 regions defined for the GTAP 8.1 database both in spreadsheet form and in GTAP's native binary file format. Finally, we provide an add-on to FlexAgg2 program to further aggregate the 134 regions as desired. Our analysis makes substantial refinements to the estimates of carbon stocks used for modeling carbon emissions from indirect land use change. The spatial detail of our analysis is a major advantage over previous databases because it provides estimates tailored to the regions of interest and better accounts for the variation of carbon stocks across the landscape, and between wetland and non-wetland regions.

EXECUTIVE SUMMARY

This report summarizes the results of a geographically-explicit analysis of soil and biomass carbon stocks that significantly refined estimates of carbon stocks used by global economic models such as the Global Trade and Analysis Project (GTAP), which is frequently used to estimate carbon emissions from indirect land use change (ILUC). Previous modeling efforts relied on biomass and soil carbon stocks from the Woods Hole Research Center (WHRC) database, which is based on an extensive literature review by R.A. Houghton (See Gibbs et al. 2007 for synthesis of data sources). The WHRC data are not spatially explicit but rather provide a look-up table of average values across 10 broad regions that are then applied to many agro-ecological zones (AEZ). The version of the Global Trade Analysis Project (GTAP) model currently used by Purdue University researchers for ILUC modeling, GTAP-BIO-ADV, uses regions and AEZs that are much more detailed than the broad WHRC categories. Thus a given WHRC value is applied across the 203 unique GTAP regions (e.g., Tyner, Taheripour et al. 2010). A substantial amount of information is lost because of the coarse land cover categories in the WHRC look-up table. This is particularly problematic because the WHRC regions do not translate cleanly into the GTAP regions.

We synthesized a range of geographically-explicit forest, grassland and cropland biomass and soil carbon input data sources and used geographic information systems (GIS) software to create new estimates of the average amount of carbon stored in soil and biomass in each of 246 countries, stratified by 18 AEZs. We initially aggregated these data to the 134 regions defined for the GTAP-8 database, then further aggregated these values to the 19 regions used in the GTAP-BIO-ADV model. The resulting data are used in a carbon emissions accounting model to estimate CO_2 emissions from indirect land use change as predicted by GTAP (Plevin et al 2013). The spatial detail of our analysis is a major advantage over the WHRC look-up table because it provides estimates tailored to the regions of interest and better accounts for the variation of carbon stocks across the landscape.

We provide the country-level data in spreadsheet form. The versions of the data that are aggregated to 134 GTAP-8 regions and 19 GTAP-BIO-ADV regions are available both in spreadsheet format and in GTAP's native binary file format. We provide an add-on to the GTAP FlexAgg2 program (Villoria and McDougall, 2012) to further aggregate the 134 regions as desired. This new database provides a flexible framework that can be revised through future regional updates, and used with a range of emissions factor assumptions that evolve over time. Carbon stock estimates for other pools including litter, understory vegetation, harvested wood products and peat soil carbon stocks are discussed in the companion report documenting the AEZ Emissions Factor model (Plevin et al. 2013).

Land use conversion and pools are described in complementary papers on bringing land into focus for global economic models (Gibbs 2011, Gibbs et al submitted).

Our new estimates significantly improve data options for estimating carbon emissions from ILUC, building upon the geographically-explicit led by Winrock International for the US Environmental Protection Agency's (EPA) Renewable Fuel Standard (Harris et al 2009). Spatial comparison between our results and those used by the Harris et al (2009) and IPCC Tier-1 Default values indicates that our range is reasonable. We recommend updating the estimates of carbon stocks as new databases are published, as well as other minor refinements through time.

1. METHODS OVERVIEW

We used ArcGIS software to estimate the soil and biomass carbon stocks for forest, grazing land and cropland by overlaying national and AEZ boundaries on a range of geographically-explicit data sources to produce a database with values for 246 nations, stratified by 18 AEZs. We aggregated the national data to match the 134 regions defined in the GTAP-8 database by totaling the carbon in each combined region-AEZ combination and dividing these values by total area representing each carbon pool. The national-level data were then further aggregate to the 19 regions used in the GTAP-BIO-ADV model to determine the final carbon estimates (Figure 1). We created 203 regions[4] by combining the two maps, but because the resolution is coarse, there are several extremely small regions that could be integrated into nearby regions in the future.

To create the country-level data, Country-AEZ maps were overlaid with the soil and biomass carbon maps for each region using geographic information systems software, and the average carbon stocks were calculated for each region (weighted by the area of the cropland, pasture, or forest). Note that using an average value assumes that land selection is random across each land cover class or that carbon stocks vary little across the landscape. In reality, conversion will not occur randomly so the associated carbon stocks of the actually converted land could be higher or lower than the average (Gibbs et al 2007). Estimates could be improved in the future by mapping forest conversion probability and then estimating carbon stocks for the forests most likely to be cleared.

We provide separate biomass and soil carbon stock estimates for wetland and non-wetland regions to account for the great variation between these two types of soils (Figures A1, A2). The separation also ensures compatibility with economic models that often exclude wetlands and deserts from analysis assuming that they will not be converted (e.g.,

[4] While the combination of 19 regions and 18 AEZs yields 342 distinct combinations, most regions contain only a small subset of the 18 possible AEZs.

Hertel et al. 2010, Tyner et al. 2010). Two global wetlands maps were combined and used as the filter: the USDA Global Wetlands Map (Reich 1997), and the Global Lakes and Wetlands Database (GLWD) created by the Center for Environmental Systems Research in Kassel, Germany (Lehner and Döll 2004). The GLWD provides raster data with more recent information, higher spatial resolution, and more detailed classes of wetlands (Table A1). However, we used both the USDA wetlands dataset and the GLWD to capture more wetland areas. In Indonesia and Malaysia we applied an additional filter to exclude lands with >500 Mg C/ ha to ensure that we removed most peat lands following methods in Gibbs et al (2008). We also removed deserts using the FAO ecofloristic zones (Figure A3).

Agricultural conversion of wetlands remains common, particularly in Indonesia and Malaysia, and we encourage the inclusion of these regions as economic models evolve to incorporate these specific land categories. Separate wetland and peat land soil carbon values should be used if models allow conversion of those areas. We summarize literature values literature values for peatlands and wetlands in Table 1 in addition to our spatially explicit values[5].

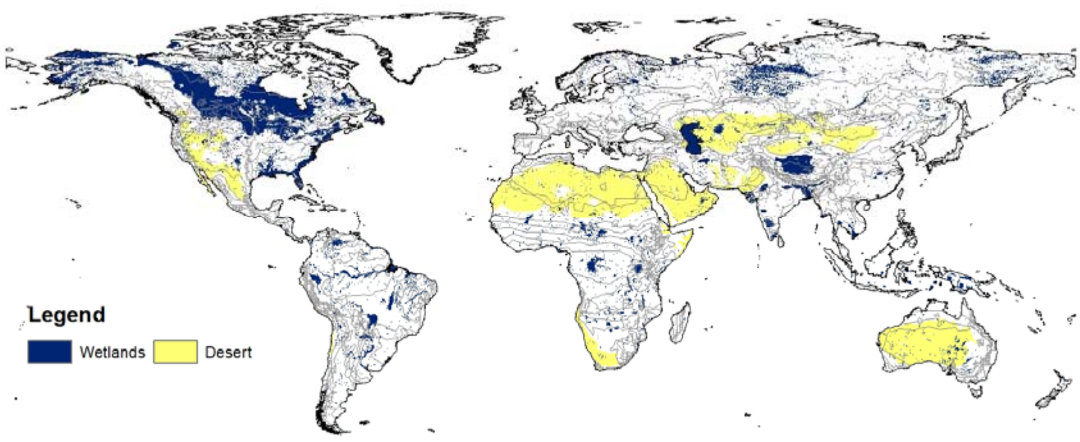


Figure 4. Combined filter used to exclude area from the soil carbon analysis comprised of GLWD wetlands, USDA wetlands and FAO deserts.

[5] Wetlands cover an estimated 4-6% of the global land area, but contain 350-530 Pg C of carbon or 20-33% of the world's soil carbon stock (Mitra et al 2005, Gorham 1995, Page et al 2008, Micker 2013). Global wetland carbon density ranges from 200-710 t C/ha (Mitra et al 2005). Much of the carbon storage is in peatlands in the boreal and temperate region (Table 1). Temperate and boreal regions have the greatest extent of peatland, but the tropical/subtropical regions have the highest carbon density (Table 1).

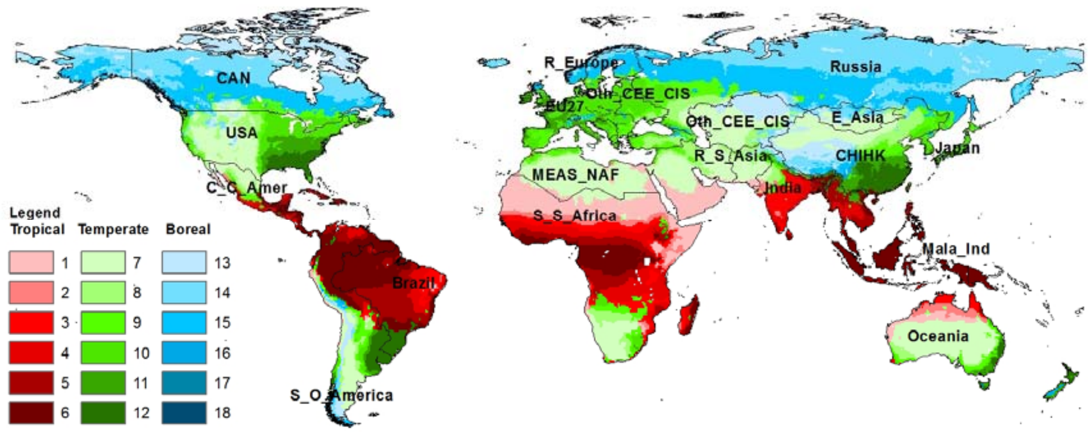


Figure 1. 19 GTAP regions combined with the 18 AEZs

2. SOIL CARBON

We used the Harmonized World Soil Database[6] (HWSD) Version 1.1[7] to estimate soil carbon stocks for forest, pasture and cropland (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009). Soil carbon stock estimates and soil information in general have long been considered highly uncertain, and the HWSD makes major improvements by integrating existing regional and national soil information worldwide into a harmonized format. This constitutes the best available spatially-explicit soil carbon data for most regions. The HWSD database relies on four different geographically-explicit data sources, including the Soil Map of the World, SOTER[8] Regional Studies, European Soil Database, and a Soil Map of China, and is considered the best available representation at the global scale. However, notable exceptions include the USA, Canada, and Australia, for which the HWSD version does not include available national data[9].

The HWSD spatial data have several soil-mapping units; each unit includes the share as a percentage of the type of soil in the given unit, as well as carbon content, depth,

[6] http://www.iiasa.ac.at/web/home/research/modelsData/HWSD/HWSD.en.html

[7] Version 1.2 was released in 2012 and a significant change is the addition of different bulk density estimates. HWSD 1.1 only had one bulk density estimate, which was derived from equations from Saxton et al (1986) based on soil texture only. The update (HWSD 1.2) includes bulk density information from SOTER database, which is based on soil texture, organic matter content, and porosity. It is noted in the documentation that the Saxton et al (1986) estimates are generally reliable but they tend to overestimate bulk density for soils with high porosity or high in organic matter.

[8] http://www.isric.org/projects/soil-and-terrain-database-soter-programme

[9] USA: NRCS US General Soil Map http://ncgc.nrcs.usda.gov/products/datasets/statsgo, Canada: Agriculture and Agri-Food Canada: The National Soil Database (NSDB) http://sis.agr.gc.ca/cansis/nsdb and Australia: CSIRO, natural Heritage Trust and National Land and Water Resources Audit: ASRIS http://www.asris.csiro.au/index_other.html, and with the recently released SOTER database for Central Africa (FAO/ISRIC/University Gent, 2007).

bulk density and several other characteristics needed to calculate the soil carbon. We used equations from Guo and Gifford (2008) to convert the information in the HWSD into soil carbon estimates[10]. The HWSD provides estimates of soil carbon stocks at both 30cm and 100cm depths (Figures 2, 3) and we provide estimates for both depths.

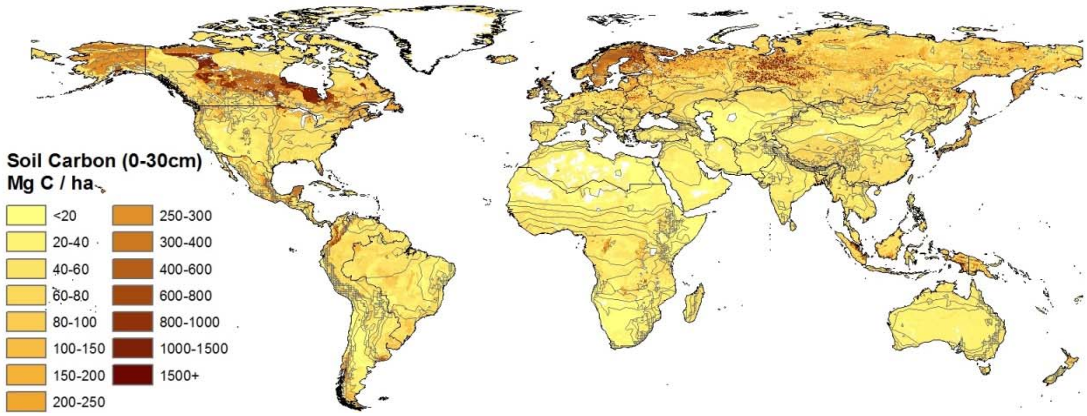


Figure 2. Harmonized World Soil Database soil carbon estimate 0-30cm

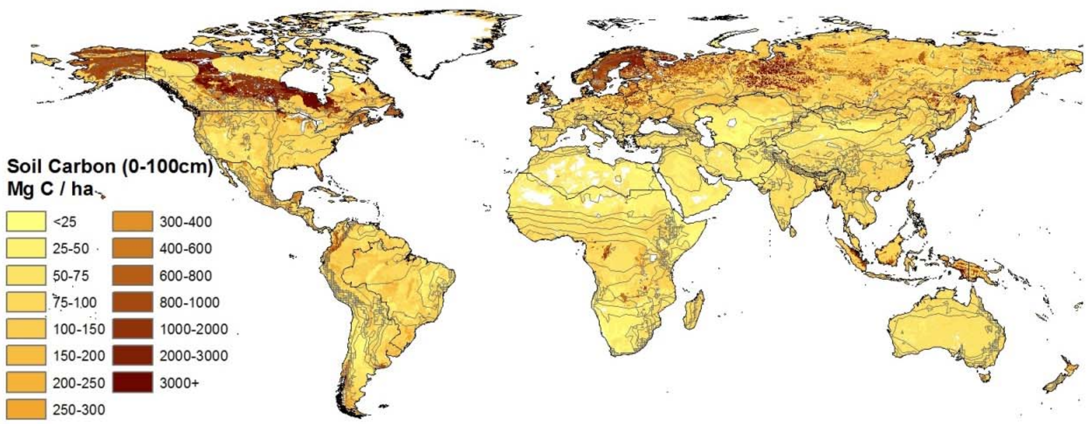


Figure 3. Harmonized World Soil Database soil carbon estimate 0-100cm

2.1 Forest soil carbon stocks

We used regional land cover maps from the forest biomass carbon datasets with the HWSD dataset to estimate forest soil carbon in most cases. For some tropical regions[11]

[10] Ct = BD * CC% * D; Ct = Total soil carbon stock (t C ha-1); BD = Bulk Density (g cm-3); CC% = % carbon content, D = Depth (cm); CC% = 0,58*OM%; OM% = % organic matter
BD = 100/ ((%OM/0.244) + ((100 - %OM)/1.64)))

[11] Saatchi et al 2011data used. See section 3.1 Forest biomass carbon

forests and non-forests were not delineated in which cases we used a MODIS forest cover map based on imagery collected from 2007-2010 to subset the forest carbon stocks from the broader HWSD map (Figure 5). Professor Mark Friedl, who directs the MODIS Land Cover Science Team at Boston University, created this map by using the most stable forest pixels to ensure we could estimate soil carbon for forest only, rather than a mix of vegetation types. We estimated forest soil carbon at the 30cm (Figure 6) and 100cm depth (Figure 7). Desert and wetland filters were used for the forest soil carbon estimates for consistency with the other soil carbon estimates.

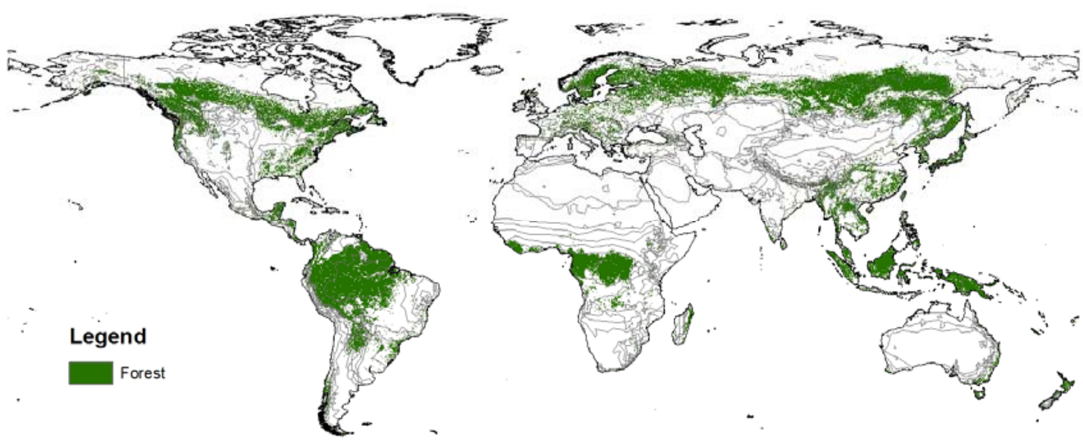


Figure 5. Forest map based on the most stable forest pixel subset from MODIS imagery collected 2007-2010 (data courtesy of Mark Friedl and Damien Sulla-Menashe, Boston University)

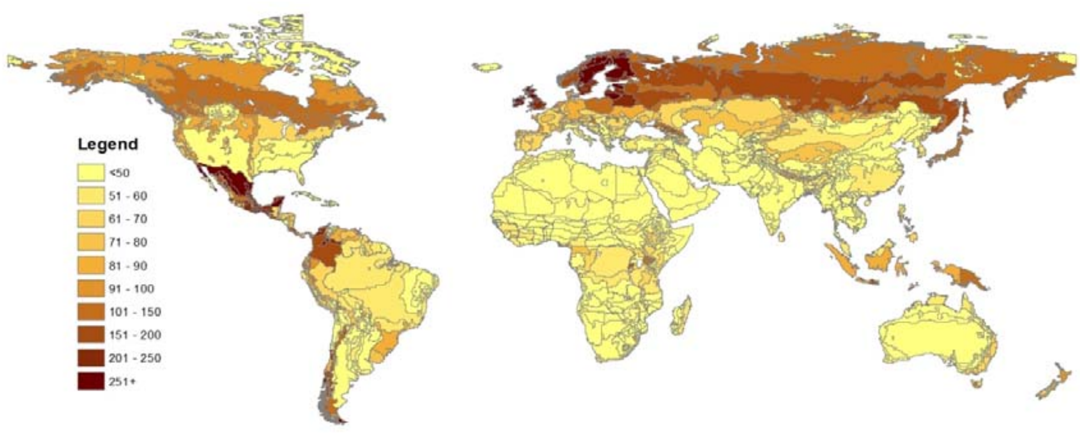


Figure 6. Weighted average forest soil carbon stocks by Country-AEZs at 30cm depth (excluding wetlands)

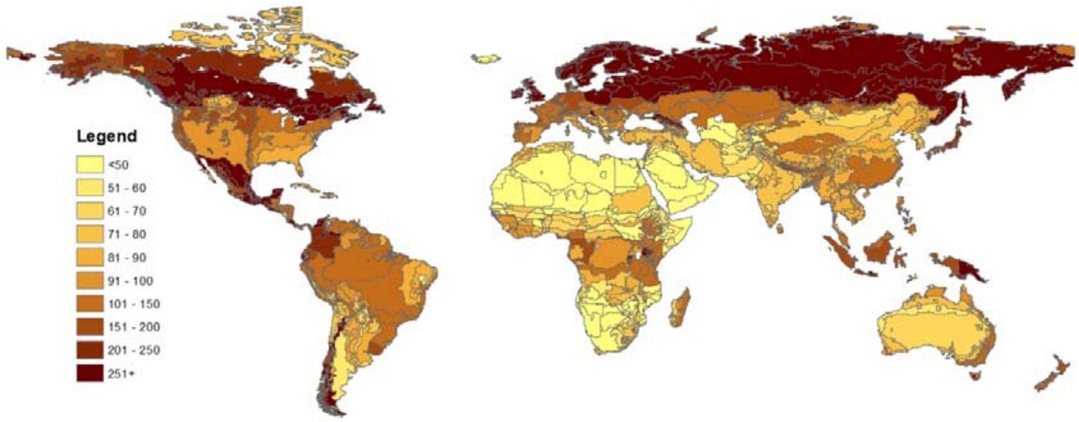


Figure 7. Weighted average forest soil carbon stocks by Country-AEZs at 100cm depth (excluding wetlands)

2.2 Pasture soil carbon stocks

We used a map of pasture to subset the soil carbon map for pastures. GTAP now uses the M3 beta version (formerly referred to as the SAGE data) for cropland and pasture, circa 2004 (Ramankutty and Foley 1999, updated). However, these land cover data are at 0.5-degree resolution, which means that most pixels have several land cover categories intermingled. Our aim is to estimate soil carbon stocks for pasture pixels as pure as possible so we opted to use an earlier version of the M3 dataset, circa 2000 (Ramankutty et al. 2008) because of its finer, 5-minute spatial resolution. These data are continuous with values ranging from 0-100% so we had to impose boundaries to convert them to discrete information. In order to identify pure pasture carbon stocks, we started with a 66% threshold, which indicates that most of the area is covered by pasture, and then successively lowered it to include 50%, 25%, and finally 10% for those regions with lower pasture coverage (Figure 8). A region had to have at least 1% of its area covered by pasture at a given threshold or a lower one was used. Some regions did not have any pasture and we used expert judgment to assign logical values from other regions (Tables 2 and 3). We estimated pasture soil carbon by GTAP-AEZ at the 30cm (Figure 9) and 100cm depth (Figure 10).

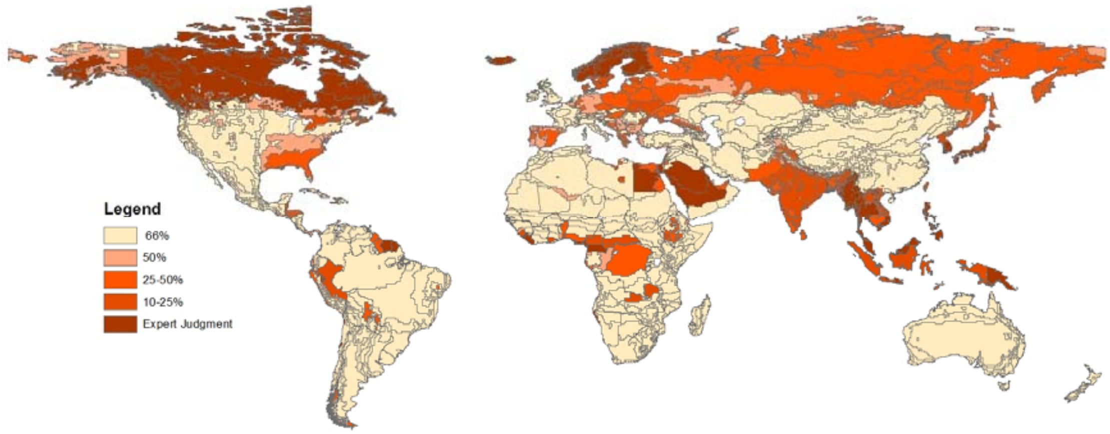


Figure 8. Pasture thresholds based on Ramankutty and Foley (1999; updated) used for soil carbon estimates

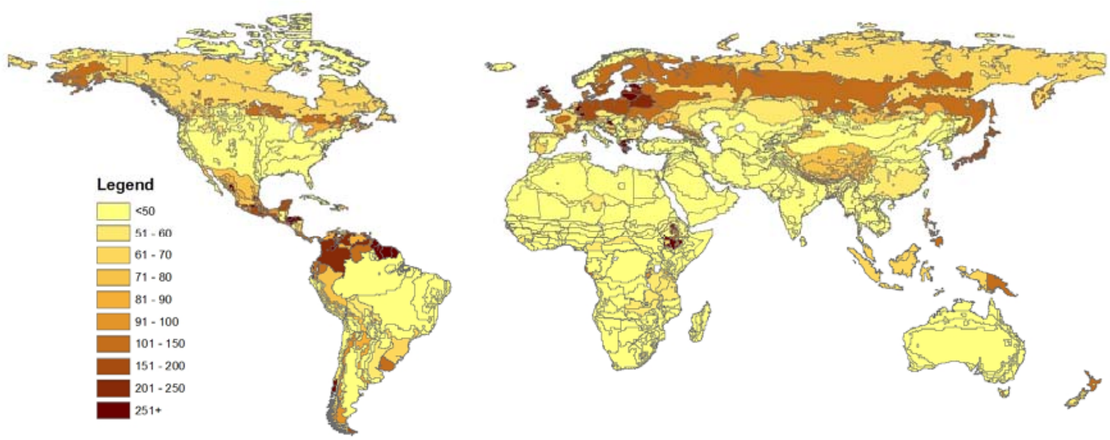


Figure 9. Weighted average pasture soil carbon stocks by Country-AEZs at 30cm depth (excluding wetlands)

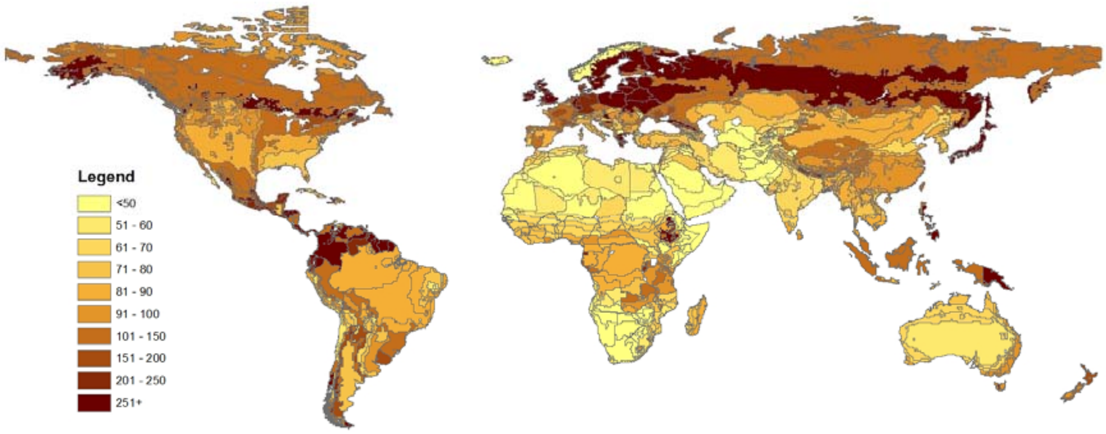


Figure 10. Weighted average pasture soil carbon stocks by Country-AEZs at 100cm depth (excluding wetlands)

2.3 Cropland soil carbon stocks

As described in Section 2.2, we used an earlier version of the M3 dataset, circa 2000, (Ramankutty et al. 2008) to identify the locations of croplands to help ensure pure cropland pixels. These data are continuous with values ranging from 0-100% so we had to once again define thresholds to convert them to discrete information. To identify pure cropland carbon stocks, we started with a 66% threshold, and then lowered it to include 50%, 25%, and finally 10% for those regions with lower cropland coverage (Figure 11). A region had to have at least 1% of the area covered by cropland at a given threshold or a lower threshold was used. Some regions did not have any cropland and we used expert judgment to assign logical values from other regions. We estimated cropland soil carbon by GTAP AEZ at the 30cm (Figure 12) and 100cm depth (Figure 13). Note that these soil carbon values are likely an overestimate as soil carbon is released when land is converted to croplands and tilled in the vast majority of cases.

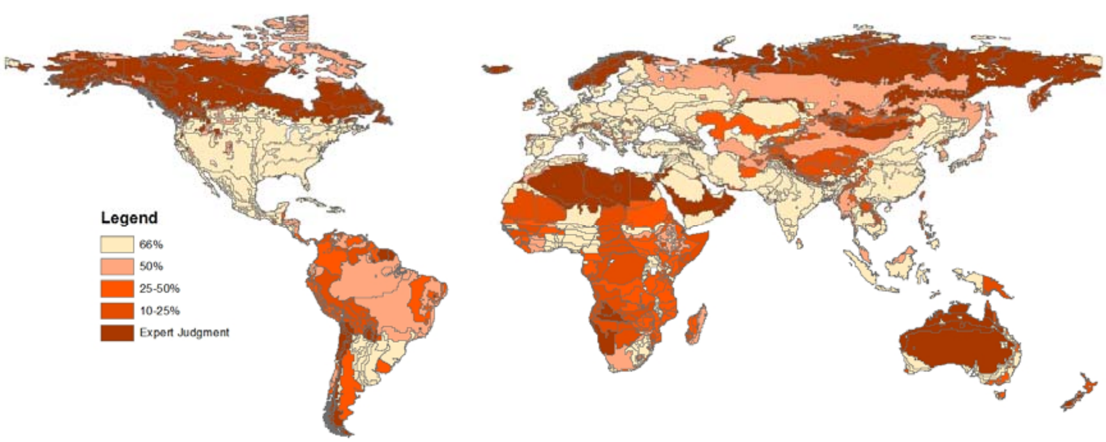


Figure 11. Cropland thresholds based on Ramankutty and Foley (1999; updated) used for soil carbon estimates

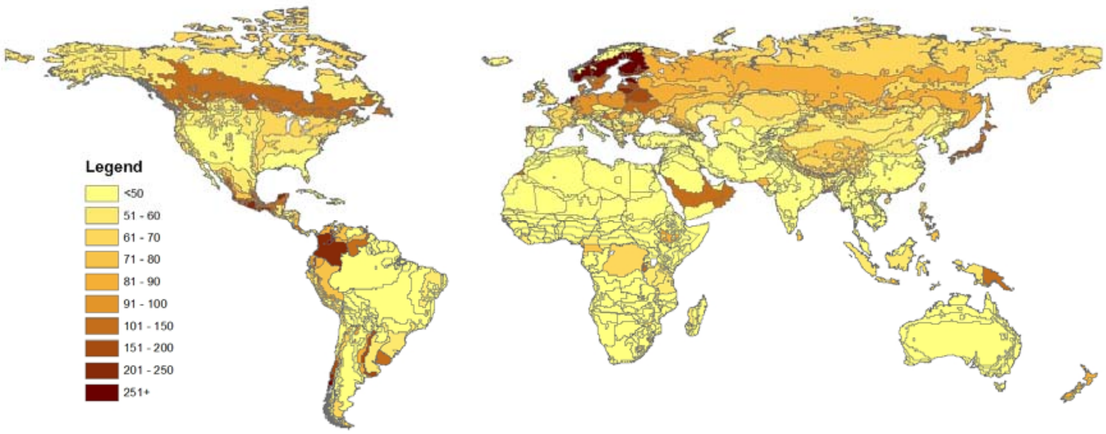


Figure 12. Weighted average cropland soil carbon stocks by Country-AEZs at 30cm depth (excluding wetlands)

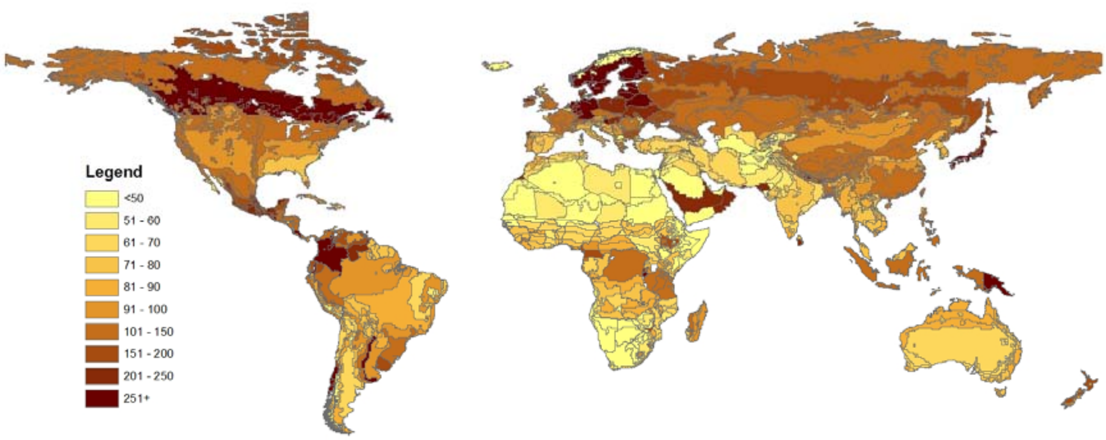


Figure 13. Weighted average cropland soil carbon stocks by Country-AEZs at 100cm depth (excluding wetlands)

3. ABOVEGROUND AND BELOWGROUND LIVING BIOMASS CARBON

We estimate living aboveground and belowground biomass only[12]. Other carbon

[12] Note that wetlands and deserts were not excluded from the biomass estimates as they were for soil carbon.

pools, including deadwood, understory vegetation and litter, as well as cropland carbon stocks, are discussed in Plevin et al. (2013).

3.1 Forest biomass carbon

We used a range of geographically-explicit datasets to estimate the living aboveground biomass (AGB), which includes trunks, branches, and leaves, and the belowground living biomass (BGB) stored in roots (Figure 14). We identified the best available spatially explicit databases, and encourage updating of this effort as new datasets become available. In many cases, we used the only carbon stock maps available for a given region. Light Detection and Ranging (Lidar) remote sensing data are ideal to estimate the spatial distribution of aboveground forest biomass carbon, but the technology is only available on airplanes (not satellites), which greatly limits the coverage. Consequently, investigators are using a range of available sensors and methods to estimate the spatial distribution of biomass in lieu of the Lidar ideal. The datasets used here are described below (Figure 15). Desert and wetland filters were applied to all forest biomass carbon estimates. An additional 500 mg C/ha filter to ensure that we captured all the wetlands in Indonesia and Malaysia.

It was not possible to have separate belowground and aboveground biomass layers specific for each dataset because not all databases provide this information separately (e.g., Ruesch and Gibbs 2008, Houghton et al 2007). Several methods were used to create separate above- and below-ground biomass values:

- For data from Saatchi et al. (2011), we created a look-up table based on the allometric equation described below to estimate root-to-shoot ratios[13].
- For boreal forests and tropical forests with data from sources other than Saatchi et al. (2011), we used root-to-shoot ratios based on total tree biomass from the widely used IPCC GPG (IPCC 2006)[14], as shown in Table 4. Note that AEZs 1-6 indicate tropical regions, and AEZs 13-18 indicate boreal regions. In some cases, the values were averaged as the translation between AEZs and the IPCC ecological zones were not exact.
- For temperate forests a root-to-shoot ratio of 0.25 was assumed in all cases.

Tropics

A state-of-the-art map of forest biomass from Saatchi et al. (2011) was used to estimate carbon stocks in the tropics. Saatchi et al. (2011) used global forest height data measured by the Geoscience Laser Altimeter System (GLAS) onboard the Ice, Cloud and

[13] Root-to-shoot ratios relate the belowground biomass quantities to the aboveground biomass. They are routinely used because aboveground biomass in an easier quantity to measure through field plots or remote sensing imagery. The correlations between above and belowground biomass are established through detailed field analysis at a limited number of plots (harvesting, drying and weighing the entire plant to weight the biomass).

[14] Using Table 4.4, references included Mokany et al 2006, Lie et al 2003, and Fittkau and Klinge 1997

land Elevation Satellite (ICESat) along with other remote sensing and ground-based data to model the spatial distribution of aboveground forest biomass. Data were calibrated and validated using 4,079 inventory and research plots. Belowground biomass in roots was estimated from aboveground biomass using an allometric equation[15] developed from literature ($BGB = 0.489AGB^{0.89}$). We assumed a carbon fraction of 0.50 to convert biomass to carbon stocks (IPCC 2006). The Saatchi et al (2011) map has 1km spatial resolution. The Saatchi data biomass data did not delineate between forest-nonforest biomass and did not include a landcover map, therefore a MODIS land cover map was applied to extract forest lands. The map below shows the Saatchi boundary map for the tropics. In some cases Saatchi data was not available for an entire region. In this case, the forest area for the country-aez region was estimated for both Saatchi and Ruesch and Gibbs. The dataset with more forest coverage was used for the forest biomass carbon estimate and land cover for the forest soil carbon.

United States

The National Biomass and Carbon Dataset for the year 2000 produced at the Woods Hole Research Center was used to estimate forest carbon stocks in the United States (Kellndorfer et al. 2011). The dataset was created based on an empirical modeling approach. It combined the USDA Forest Service Forest Inventory and Analysis (FIA) data with high-resolution InSAR data from the 2000 Shuttle Topography Mission (SRTM) and Landsat ETM+ satellite data. We assumed a carbon fraction of 0.50 to convert biomass to carbon stocks. The map has a 30m spatial resolution. We used the IPCC Tier-1 default root-to-shoot ratios to add in BGB because the National Biomass and Carbon Dataset 2000 (NBCD2000) only included AGB. Note that the NBDC2000 dataset is only for the conterminous U.S. but we have also applied it to Alaska. Values for Canada would be more accurate but we were unable to make that distinction without adjusting the average values for the entire U.S. We ranked accuracy for the conterminous US over Alaska because we assume fewer ILUC impacts in Alaska[16].

Russia

A map of forest biomass based on MODIS satellite imagery calibrated with forest inventory data was used to extract data for Russia (Houghton et al. 2007). Houghton et al (2007) mapped the distribution of living forest biomass for the year 2000 by developing a statistical relationship between MODIS satellite imagery and ground measurements of forest biomass at twelve field sites. They converted forest growing stock, which includes ABG, BGB, and understory carbon, measured by the inventory data to biomass using allometric equations by Alexeyev and Birdsey (1998) and assumed a 0.50 carbon fraction to convert biomass to carbon stocks. The map has a 500m spatial resolution. It is important

[15] An allometric equation or correlations predicts biomass on the basis of one or more measurements of the vegetation such as relating aboveground biomass to belowground biomass, of tree height to total biomass.

[16] Note Kellndorfer data used for the US only has data for the conterminous US but the soil carbon estimates include Alaska soil carbon data. There is also significant forest cover in the US therefore we used the R&G data to estimate forest area and added it to the conterminous forest area estimates.

to note that the error in biomass estimates was ~40%, indicating that only ~60% of the variation in predicted biomass was explained by the regression model. The authors describe their results as partially successful.

European Union, Canada, Australia and Other regions

The Ruesch and Gibbs (2008) global biomass carbon map was used for regions where other options were lacking. The biomass map applies the International Panel on Climate Change (IPCC) Tier-1 default values for AGB and BGB to the Global Land Cover (GLC2000) map for the year 2000, which has a spatial resolution of 1km. Specifically, Ruesch and Gibbs (2008) synthesized and mapped IPCC Tier-1 default values using the global land cover map stratified by continent, ecoregion and forest disturbance level. They used a carbon fraction of 0.47 to convert from biomass to carbon. Note that this dataset does not account for spatial variation within forest categories as captured by the satellite-based approaches used in other regions.

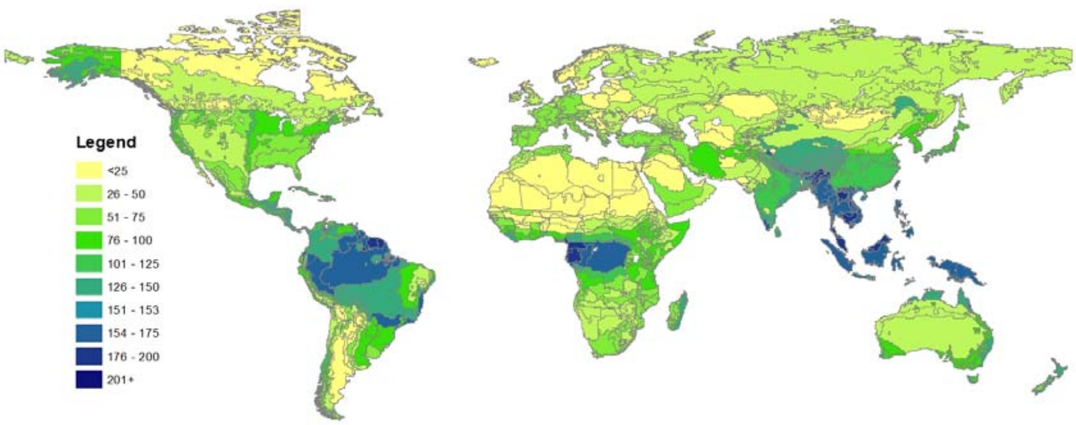


Figure 14. Weighted average forest biomass carbon stocks by Country-AEZs (Mg C / ha) (excluding wetlands)

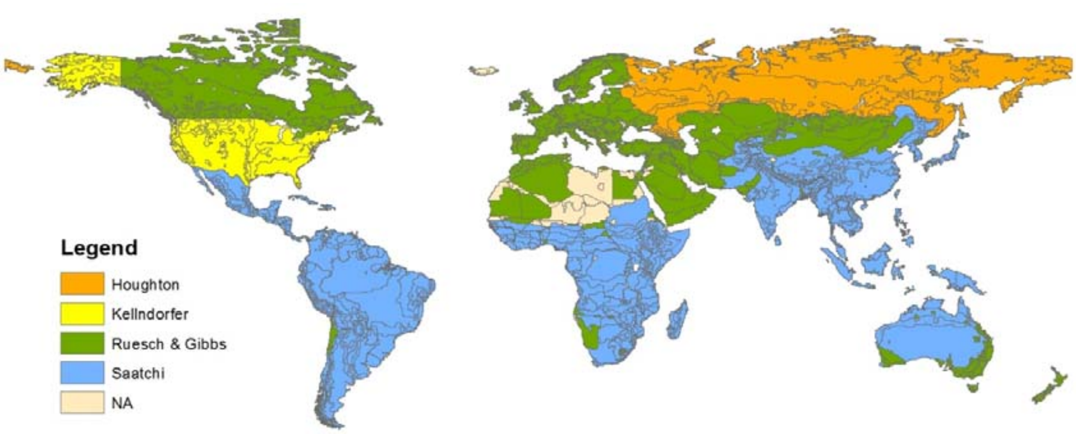


Figure 15. Sources for geographically-explicit forest biomass data

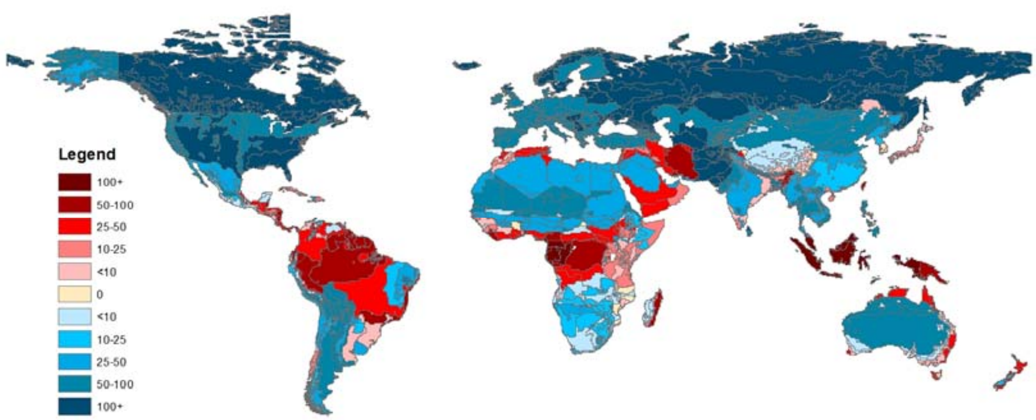
3.2 Pasture biomass carbon

Pasture and grassland biomass varies widely within any region driven by rainfall and soil texture but there are few publications on carbon stocks of managed grasslands that can be scaled up and consistently applied across large regions. In this case, we applied the IPCC Tier-1 default values for grasslands[17], which vary by ecofloristic zones (Table 5) and assume a 0.47 carbon fraction. Consequently the pasture biomass values are weaker than the forest biomass and soil carbon estimates that were based on more spatially detailed datasets in most cases. Note that we did not estimate carbon stocks for the Brazilian cerrado or other areas of unmanaged shrubland, grassland or savanna. These would have much higher carbon stocks (20-75 Mg / ha) but are omitted because they are excluded from GTAP-BIO (Gibbs 2011). Satellite-estimated net primary productivity may be a way to improve estimates of pasture biomass carbon stocks in the future.

4. DISCUSSION

The soil and biomass carbon stock analysis presented here provides a refined basis to estimate carbon emissions from ILUC. We conducted a simple spatial analysis to identify differences between our results and studies used elsewhere.

We compared our updated values with the WHRC values used in Hertel et al. (2010) and Tyner et al. (2010) (Figure 16). Our values were higher around the Amazon basin, humid tropical Africa, and insular Southeast Asia. WHRC values were substantially higher (50+ Mg C / ha) in the US, Canada, Europe, and Russia. (Table A2).



[17] Tables 6.1 and 6.4

Figure 16. Difference in forest biomass carbon between our geographically-explicit estimates and WHRC values applied to map of GTAP Countries-AEZ (Mg C / ha).
Red = our geographically-explicit estimates higher than WHRC values,
Blue = our geographically-explicit estimates lower than WHRC default values.

In order to further examine the differences between prominent estimates of forest carbon stocks we also compared a GTAP country-AEZ weighted average forest carbon map based on Ruesch and Gibbs (2008), which applied IPCC Tier-1 default values to a land cover map, to our results based on a range of datasets (Figure 14). Across Latin America, Africa and insular Southeast Asia, our estimates based on Saatchi et al. (2011) are 10-50 t C / ha lower than the IPCC Tier-1 default values (Figure 16). The Saatchi dataset is spatially-explicit and thus captures a range of forest conditions, including gaps due to streams, dead trees, and other sources of heterogeneity. These are averaged together across a single pixel. This averaging could lead lower or higher values than would be obtained by applying a single default value across a pixel that likely captures minimum heterogeneity.

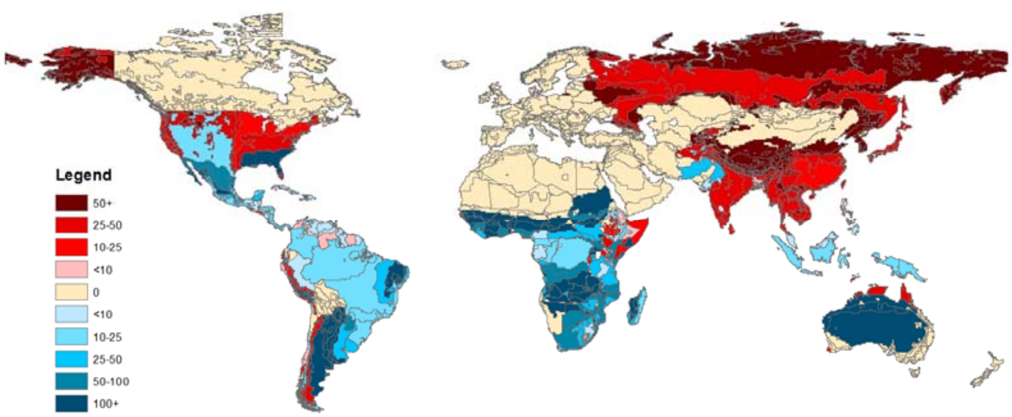


Figure 17. Difference in forest biomass carbon between our geographically-explicit estimates and IPCC Tier-1 values applied to forest map by Ruesch and Gibbs (2008).
Red = our geographically-explicit estimates higher than IPCC Tier-1 default values,
Blue = our geographically-explicit estimates lower than IPCC Tier-1 default values,
Beige = no difference: this study used Ruesch and Gibbs 2008 IPCC Tier-1 estimates.

Lastly, we compared our sources of forest biomass estimates with those used by Harris et al. (2009) for the US EPA in Table 6. Overall, our approach relied on more recently published data sources, particularly for the tropics, and improved upon the framework established by Harris in some instances. A comparison between the Harris values produced at the state level and our values estimated at the GTAP-Region-AEZ level is difficult because different scales are involved. However, general patterns can be observed. For example, our values are higher across most of the tropics but lower in Brazil. Our values were lower in Australia, Europe and Asia but mixed in the United States. Winrock used the HWSD to estimate soil carbon stocks as we did. Note that the Winrock estimates for soil carbon are for forests only, while we provided estimates for forest, cropland and pasture separately.

While we have provided the best available estimates for forest biomass carbon stocks available, it is important to note that uncertainty remains. The estimates we provide may under- or overestimate the values on the ground because of spatial variability. The science of mapping forest carbon stocks has improved considerably, but more attention has been focused on estimating changes in forest areas rather than their carbon stocks. In addition, our approach used a weighted average of forest carbon stocks within a region, and the actual value of any given forest may be higher or lower than the average. The HWSD soil database does not account for land use history in many cases, and this can have a great impact on soil carbon content.

5. CONCLUSIONS

Our analysis provides a substantial improvement for carbon stock estimates for global economic models, and will provide more realistic estimates of carbon emissions from market-mediated land use change. We are actively improving the analysis and anticipate publishing a version 2.0 that will include the following improvements: 1.) Distinguish between accessible and inaccessible forests[18], 2.) Separate ABB and BGB, 3.) Additional land categories as the global economic models evolve, 4.) Update soil carbon estimates with the recently refined HWSD v2, and regional soil carbon databases for the U.S., Canada, and Australia that likely improve upon the HWSD for those regions.

[18] Accessible forests are those more likely to be cleared due to proximity to roads, towns, agriculture, and other factors. Inaccessible forests are less likely to be cleared as they are in protected areas, in mountainous regions too difficult to cultivate etc.

TABLES

Table 1. Wetland carbon stock by region

Region	Area (Mha)	Total carbon (Gt C)	Carbon density (t C ha)	Source
Boreal/subarctic	346	273-455	789-1315	Turunen et al 2002; Gorham 1991
Temperate	350	455	1300	Micker 2013
Tropical/sub-tropical				
Southeast Asia	27	42-55	1555-2037	Hooijer et al 2010; Yu et al 2010
South America	4.5	13-18	2888-4000	Yu et al 2010

Table 2. Portion of region covered by each pasture and cropland threshold (GTAPAEZ)

Land Cover	Threshold	% of GTAPAEZ
Crop	66%	54%
	50%	10%
	25-50%	11%
	10-50%	11%
	Expert Judgment	17%
Pasture	66%	60%
	50%	6%
	25-50%	13%
	10-25%	9%
	Expert Judgment	15%

Table 3. Portion of region covered by each pasture and cropland threshold (GTAP-Country)

Land Cover	Threshold	% of GTAPAEZ
Crop	66%	38%
	50%	7%
	25-50%	14%
	10-50%	8%
	Expert Judgment	32%
Pasture	66%	37%
	50%	5%
	25-50%	13%
	10-25%	5%
	Expert Judgment	40%

Table 4. Root-to-shoot ratios for forest used in this study

AEZ	< 125 tonnes biomass	> 125 tonnes biomass	< 75 tonnes biomass	> 75 tonnes biomass	Default value
1	0.56	0.28			
2	0.56	0.28			
3	0.20	0.24			
4	0.20	0.24			
5	0.37	0.37			
6	0.37	0.37			
7					0.25
8					0.25
9					0.25
10					0.25
11					0.25
12					0.25
13			0.39	0.24	
14			0.39	0.24	
15			0.39	0.24	
16			0.39	0.24	
17			0.39	0.24	
18			0.39	0.24	

Table 5. Pasture biomass carbon stocks based on IPCC Tier-1 default values

AEZ Zone ID	Latitude	Humidity	Total C (Mg C /ha)
1	Boreal	Dry & Wet	4.3
2	Temperate	Cold, dry	3.2
3	Temperate	Cold, wet	6.0
4	Temperate	Warm, dry	3.0
5	Temperate	Warm, wet	6.8
6	Tropical	Dry	4.4
7	Tropical	Moist & wet	8.1
8	Temperate	Dry (avg cold & warm)	3.1
9	Temperate	Wet (avg cold & warm)	6.4

Table 6. Comparison between data sources used for analysis presented here and the USEPA created by Harris et al. (2009)

Parameter	This analysis (Gibbs et al 2013)	USEPA (Harris et al 2009)	Comments
Soil Carbon	HWSD	HWSD	Same
Crop Biomass	IPCC Default	IPCC Default	Same
Pasture Biomass	IPCC Default	IPCC Default & Castro and Kauffman (1998) for Brazil	Here we consider only managed pasture whereas USEPA has a broader grassland, savanna, and shrubland continuum
Forest Biomass - Tropics	Saatchi et al. (2011)	Saatchi et al (2011) for S. Am, Gibbs and Brown (2007) for Africa, & Brown et al. (2001) for SE Asia	The finalized Saatchi et al. (2011) satellite-based data were not available until after the USEPA work was completed, and represent an improvement
Forest Biomass - Russia	Houghton et al. (2011)	Houghton et al. (2011)	Same
Forest Biomass - USA	NLCD2000	Blackard et al. (2008)	NLCD2000 combines Forest Inventory Analysis (FIA) data with satellite information while Blackard et al. (2008) used the FIA directly to generate a spatially-explicit dataset
Forest Biomass - China	Saatchi et al. (2011) & Ruesch and Gibbs (2008)	Piao et al. (2008)	Piao et al. (2005) is not spatially explicit; Saatchi et al (2011) is an improvement
Forest Biomass - Europe	Ruesch and Gibbs (2008)	Naburrs et al. (2003)	Nabuurs et al. (2003) is not spatially explicit but has the strength of more regional data than Ruesch and Gibbs (2008).
Forest Biomass - Australia	Ruesch and Gibbs (2008)	Ruesch and Gibbs (2008)	Same
Forest Biomass - Canada	Ruesch and Gibbs (2008)	Ruesch and Gibbs (2008)	Same
Forest Biomass - Other	Ruesch and Gibbs (2008)	Ruesch and Gibbs (2008)	Both used Ruesch and Gibbs (2008) to fill in gaps between other, more detailed datasets

REFERENCES

Alexeyev V. A. and R. A. Birdsey. 1998. Carbon storage in forests and peatlands of Russia *General Technical Report* NE-244, USDA, Forest Service, Northeast Research Station, Radnor, PA

FAO/IIASA/ISRIC/ISSCAS/JRC, 2009. *Harmonized World Soil Database (version 1.1)*. FAO, Rome, Italy and IIASA, Laxenburg, Austria.

Gibbs, H. K, S. Brown, J. O. Niles, and J. A Foley. 2007. Monitoring and estimating tropical forest carbon stocks: making REDD a reality. Environmental Research Letters 2 (4):045023. DOI: 10.1088/1748-9326/2/4/045023.

Gibbs, H. K, M. Johnston, J.A Foley, T. Holloway, C. Monfreda, N. Ramankutty, and D. Zaks. 2008. Carbon payback times for crop-based biofuel expansion in the tropics: the effects of changing yield and technology. Environmental Research Letters 3 (3):034001. doi: 10.1088/1748-9326/3/3/034001.

Gibbs, 2011. An Analysis of the Land Use Pools and Conversion Parameters in GTAP. Report for the California Air Resources Board.

Gorham, E., 1991. Northern peatlands: role in the carbon cycle and probable responses to climatic warming. Ecological Applications 1, 182–195

Harris, N., S. Grimland, and S. Brown, 2009. Land Use Change and Emission Factors: Updates Since the RFS Proposed Rule. Winrock International. December 2009.

Hertel, T.W., A. Golub, A. D. Jones, M. O'Hare, R. J. Plevin, and D. M. Kammen. 2010a. Global Land Use and Greenhouse Gas Emissions Impacts of U.S. Maize Ethanol: Estimating Market-Mediated Responses. BioScience 60 (3):223-231.

Hertel, T.W., A. Golub, A. D. Jones, M. O'Hare, R. J. Plevin, and D. M. Kammen. 2010b. Supporting Materials for: Global Land Use and Greenhouse Gas Emissions Impacts of U.S. Maize Ethanol: Estimating Market-Mediated Responses. BioScience 60 (3):223-231.

Hooijer, A; S. Page, J.G. Canadell, M. Silvius, J. Kwadijk, H. Wosten, J. Jauhianen 2010. Current and future CO2 emissions from drained peatlands in Southeast Asia. Biogeosciences, 7, 1505-1514. Doi: 10.5194/bg-7-1505-2010

Houghton, R.A., D. Butman, A.G. Bunn, O.N. Krankina, P. Schlesinger, T.A. Stone. 2007. Mapping Russian forest biomass with data from satellites and forest inventories. Environmental Research Letters 2, 045032 (doi:10.1088/1748-9326/2/4/045032)

IPCC. 2006. IPCC Guidelines for National Greenhouse Gas Inventories. Prepared by the National Greenhouse Gas Inventories Programme ed H S Eggleston, L Buendia, K Miwa, T Ngara and K Tanabe (Japan: Institute For Global Environmental Strategies)

Kellndorfer, J., W. Walker, L. LaPoint, J. Bishop, T. Cormier, G. Fiske, K. Kirsch. 2011 The National Biomass and Carbon Dataset A hectare-scale dataset of vegetation height, aboveground biomass and carbon stock of the conterminous United States.. Data published by The Woods Hole Research Center, 2011.

Lehner, B. and P. Döll. 2004. Development and validation of a global database of lakes, reservoirs and wetlands. Journal of Hydrology 296:1-22. (http://www.worldwildlife.org/science/data/item1877.html)

Micker, R.A. 2013. Carbon fluxes and greenhouse gas emissions from wetland wildland fires in the 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands

Mitra, S., R. Wassman, Reiner; P. Vlek. 2005. An appraisal of global wetland area and its organic carbon stock. Current Science, 8(1).

Page, S; Rieley, J.O; Banks, C.J; Global and regional importance of the tropical peatland carbon pool. Global Change Biology, no.doi: 10.1111/j.1365-2486.2010.02279.x

Pravettoni, UNEP/GRI-Arendal. Peat distribution in the World. 2009. http://www.grida.no/graphicslib/detail/peat-distribution-in-the-world_8660

Plevin, R. H. K. Gibbs, J. Duffy, S. Yeh, and S. Yui. 2013. AEZ-EF: A model of greenhouse gas emissions from land-use change for use with AEZ-based economic models. Global Trade and Analysis Project (GTAP) Refereed Technical Paper Series.

Ramankutty, N. and J. A. Foley. 1999. Updated for the 1700-2007 period (www.geog.mcgill.ca/landuse/pub/Data/Histlanduse/).

Reich, P. 1997. Global Distribution of Wetlands Map. USDA NRCS Global and Regional Maps. http://soils.usda.gov/use/worldsoils/mapindex/wetlands.html

Ruesch, A. and H. K. Gibbs. 2008. New IPCC Tier-1 Global Biomass Carbon Map For the Year 2000. Available online from the Carbon Dioxide Information Analysis Center [http://cdiac.ornl.gov], Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Saatchi, S.S., N. L. Harris, S. Brown, M. Lefsky, E. T. A. Mithchard, W. Salas, B. R.

Zutta, W. Buermann, S. L. Lewis, S. Hagen, S. Petrova, L. White, M. Silman, and A. Model. 2011. Benchmark map of forest carbon stocks in tropical regions across three continents. Proceedings of the National Academy of Sciences. 108(24):9899-9904.

Turunen J., E. Tomppo, K. Tolonen, A. Reinikainen. 2002. Estimating carbon accumulation rates of undrained mires in Finland – application to boreal and subarctic regions. Holocene 12, 69-80, doi:10.1191/0959683602hl522rp

Tyner, W. E., F. Taheripour, Q. Zhuang, D. Birur, and U. Baldos. 2010. Land use changes and consequent CO2 emissions due to US corn ethanol production: A comprehensive analysis Purdue University

West, P. H. K. Gibbs, J.A. Foley, C. Barford, and J. Wagner. 2010. Trading carbon for food: global comparison of carbon storage vs. crop yields on agricultural land. Proceedings of the National Academy of Science 107(46):19627-19632.

Villoria N. and McDougall R. 2012 "FlexAgg2.0: An Improved Version of the Data Aggregation Program FlexAgg." GTAP 8 Data Base Documentation, Chapter 4. Center for Global Trade Analysis, Purdue University, IN.

Yu Z, J. Loisel, D.P. Brosseau, D.W. Beilman, S.J. Hunt. 2010. Global peatland dynamics since the Last Glacial Maximum, Geophysical Research. Letters 37, L13402, doi: 10.1029/2010GL043584

APPENDIX

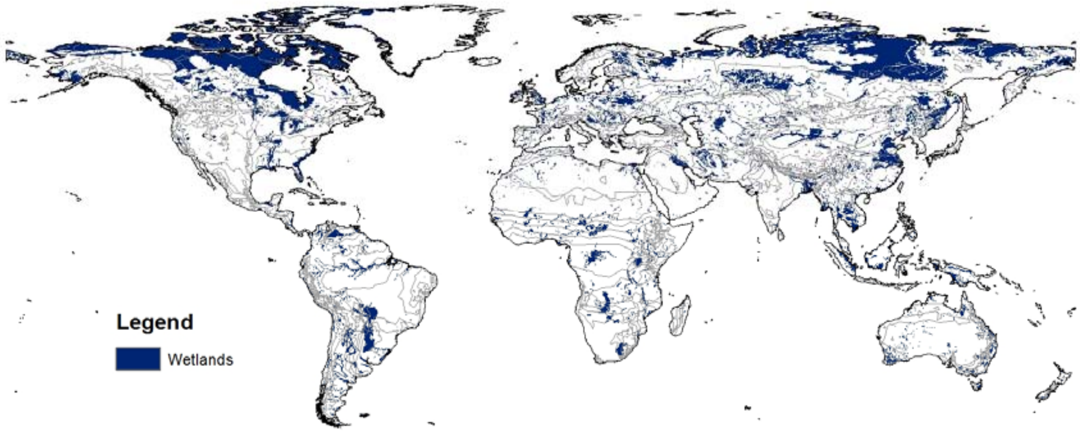


Figure A1. USDA wetlands map used as part of wetlands filter (Reich 1997)

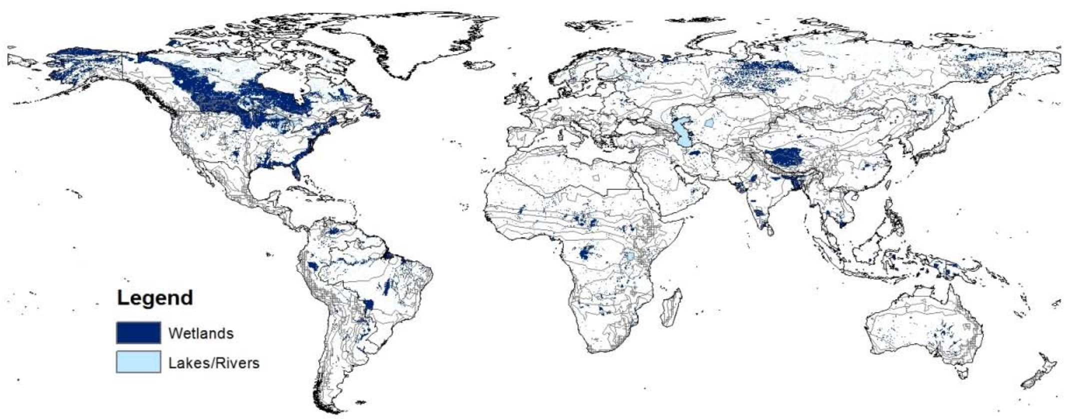


Figure A2. Global Lakes and Wetlands Database used as part of wetlands filter (GLWD; Lehner and Döll 2004).

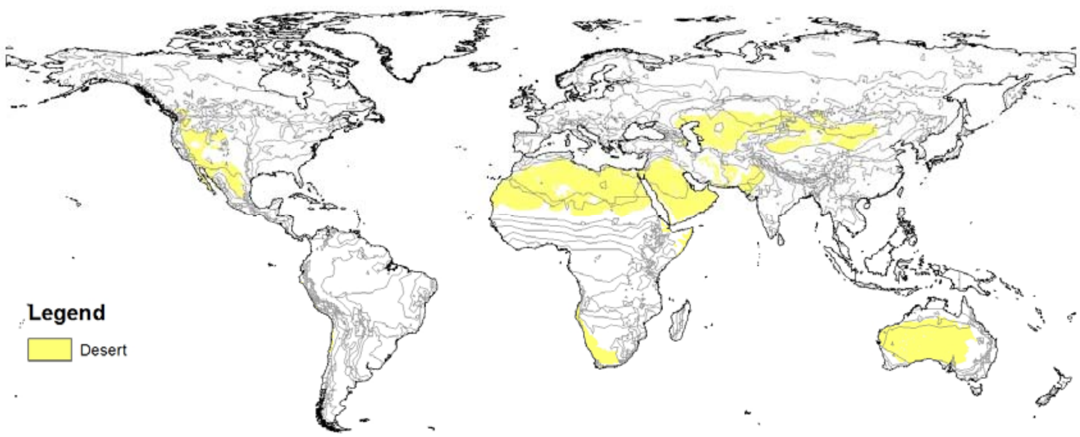


Figure A3. Desert map used as part of desert filter (FAO Ecoregion)

Table A1. Comparison of GLWD with USDA global wetland map

	GLWD (Lehner and 2004)	USDA (Reich 1997)
Date published	2004	1997
Source data	Existing maps, data, & info	FAO – UNESCO Soil Map of the World combined with soil climate map
Time period covered by source data	1992-2000 (see literature for details)	FAO/UNESCO 1971-1981; soil climate map dates unknown
Spatial resolution	1:3,000,000	1:5,000,000
Spatial resolution	0.5 minute grid cell (~1km)	2 minute grid cell (~4km)
Number of classes	9	5
Coverage	Global	Global

Table A2. Forest carbon estimates by GTAP regions based on WHRC carbon values*

GTAP	WHRC	Forest Mg C/ha**
USA	United States	171
EU27	Europe	123
BRAZIL	Latin America	91
CAN	Canada	160
JAPAN	Pacific Developed	92
CHIHKG	China India Pakistan	136
INDIA	China India Pakistan	136
C_C_AMER	Latin America	91
S_O_AMER	Latin America	91
E_ASIA	Pacific Developed	92
MALA_INDO	South & Southeast Asia	221
R_SE_ASIA	South & Southeast Asia	221
R_S_ASIA	South & Southeast Asia	221
RUSSIA	Former Soviet Union	150
OTH_CEE_CIS	Europe	123
R_EUROPE	Europe	123
MEAS_NAFR	North Africa/Mid East	27
S_S_AFR	Africa	60
OCEANIA	Pacific Developed	92

* Table from Tyner et al 2010 Table 11
** Estimates from Searchinger et al 2008 SI – Average carbon stocks in undisturbed vegetation